MAPPING DETAILED SEAGRASS HABITATS USING SATELLITE IMAGERY

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1. INTRODUCTION

Seagrass meadows are characteristic features of shallow waters worldwide and seagrass habitats are extensive in the Gulf of Mexico. These habitats provide a variety of ecosystem functions including food and shelter for many fauna, imparting stability to sediments and affecting nutrient cycling and water turbidity. In essence, maintenance of adequate seagrass cover is intimately related to coastal ecosystem health and thus monitoring of seagrass habitats is a priority of coastal managers. Overall we lack the methodology to provide rapid assessment of seagrass distribution and recognize changes in patterns of cover over large spatial scales. For decades, a variety of methods have been used for mapping and monitoring of seagrass habitats in shallow coastal waters using optical remote sensing in many locations, traditionally through the use of aerial photography and the use of moderate-resolution multispectral satellite image data: Landsat Multispectral Scanner (MSS), Thematic Mapper (TM) / Enhanced Thematic Mapper Plus (ETM+), and SPOT image data. Recent developments in digital multispectral and hyperspectral remote sensing have resulted in an increase in the use of these methods to map and monitor seabed habitats in shallow waters due to improved performance. Current methods and techniques that utilize optical remote sensing mostly classify seabed habitats into several classes and usually lack details on seagrass type or density [1]. Depending on the goals of a seagrass management program such “coarse” information may not be useful for decision making. In this study, we propose to utilize four satellite sensor image data to map detailed seagrass habitats in Pinellas County coastal areas, Florida, USA. As a preliminary test for the project, supported by NASA, USA, the objective of the test is to evaluate and compare the capability of four satellite sensor data for mapping detailed seagrass habitats.

2. STUDY AREA AND DATA SETS

The study area (28^{o}03’36”N, 82^{o}48’45”W) is located along the northwestern coastline of Pinellas County, Florida, USA. In Pinellas County three seagrass species are numerically dominant: *Syringodium filiforme*, *Thalassia testudinum*, and *Halodule wrightii*. In this study, the species assemblage is categorized as submerged aquatic vegetation (SAV). Four satellite sensor image data were analyzed. They are Landsat TM (acquired on Oct. 1, 2009), EO-1 ALI and Hyperion (HYP) (acquired on Oct. 8, 2009), and GeoEye IKONOS (IKO) (acquired on Oct. 1, 2009). Three TM and IKO visible bands, four ALI visible bands, and 24 HYP bands were used for mapping and analyzing seagrass habitats. TM, ALI and HYP visible bands have a 30-m resolution and IKO multispectral bands have a 4-m resolution. The filed data at 65 plots were collected during the September and October, 2009 and include SAV species, cover percentage, substrate types, water depth and quality measurements, etc. For this analysis, the SAV cover percentage measurement was used in two classification schemes: 3-class (Continuous: SAV cover >75%, Patchy: SAV 25-75%, No SAV: SAV <25%) and 5-class (SAV cover >75%, SAV cover 50-75%, SAV cover 25-50%, SAV cover 1-25%, and No SAV).

3. METHODOLOGY

In this study, the analysis method mainly comprises image preprocessing, calculating depth-invariant bands, determining training and test areas, classification with inputs of depth-invariant bands, and evaluating and comparing the capability of the four sensor data for mapping detailed seagrass habitats. Image processing includes converting digital number to at-sensor radiance and calibrating to surface reflectance.

Referring to models [2][3] and recent work done by [4] and [5] regarding creating depth-invariant bands for mapping and characterizing benthic habitats and coral reefs, we created visible depth-invariant bands for the four sensor data to weaken the effect of variable depth on SAV mapping. Following the processing, three depth-invariant bands, Y_{12}, Y_{13}, and Y_{23} were respectively calculated for TM and IKO sensors; six depth-invariant bands Y_{12}, Y_{13}, Y_{14}, Y_{23}, Y_{24}, and Y_{34} were calculated for ALI; and 24 depth-invariant bands were created from HYP data. HYP has more 30 visible bands. Based on the three visible wavelengths of TM and IKO, eight bands were used from each of blue, green and red spectral ranges (total of 24 bands) from HYP data. Maximum Likelihood Classifier (MLC) in ENVI4.5 [6] was employed to classify the study area in different SAV classes. Determination of adequate training and test samples was based on two aspects: 65 field plot observations and ISODATA (an unsupervised procedure) clustered results. The former observation provides with indicator of SAV classes and the latter presents spectral homogeneous patches/clusters to define regions of interest (ROIs). To evaluate and compare the capability of the four sensor data for mapping detailed seagrass habitats, the standard accuracy indicators (overall accuracy (OAA), Kappa, Producer’s and User’s accuracy) were adopted.

4. RESULTS AND ANALYSIS

With the defined training and test samples (ROIs) for two classification schemes (3-class and 5-class) and inputs of the depth-invariant bands from the four sensor images, the results were evaluated and analyzed with indicators of OAA, Kappa and both producer's and User's accuracies, calculated from test samples. The evaluation and analysis results indicate that the capability of HYP data for mapping seagrass habitats in either 3-class or 5-class scheme was consistently higher than other three sensors, followed by ALI and TM, then IKO. All sensor data present similar distribution patterns of three SAV classes, but for the 5-class scheme in Figure 1, ALI and HYP have similar spatial patterns of SAV distribution while TM and IKO have themselves similar patterns. However, their general patters are still roughly similar. The difference of the two sets of spatial distribution patterns of SAV classes (ALI/HYP vs. TM/IKO) may be due to different tidal levels and water quality between the two dates (Oct. 8, 2009 vs. Oct. 1, 2009) in the study area.

The Z-statistic tests calculated from Kappa-variance of classification results of test samples, extracted from different sensors (TM, ALI, HYP and IKO) and different schemes (3-class and 5-class) demonstrate that the differences of all accuracy indicators between the any two sensor data in the same classification schemes (3-class or 5-class) are significant at 0.99 confidence level except the difference between ALI and HYP only significant at 0.95 confidence level in the 3-class scheme and not significant at the 5-class scheme at the both confidence levels (but, it is significant between ALI and HYP at 0.90 confidence level). Given the many narrow bands in the visible region and subtle spectral information available in the HYP hyperspectral sensor data, it is not surprising that HYP sensor has the highest capability among the four sensors to map the detailed seagrass habitats. Give the fact of high variation [7] of spectrum within individual classes for high resolution IKO data, it seems reasonable that IKO sensor produced the lowest accuracies for mapping seagrass habitats in such a particular case. ALI, due to one more additional blue band, outperformed TM for mapping seagrass in this study.

5. PRELIMINARY CONCLUSIONS

In this study, with the depth-invariant bands, calculated with the ratio of attenuation of coefficients from the two radiance linearised visible bands relative to water depth, the four satellite sensor data were used to map detailed seagrass habitats. The experimental results indicate that HYP sensor has produced the best mapping results of seagrass habitats in the two classification schemes: 3-class (OAA=96%, Kappa=0.936) and 5-class (OAA=79%, Kappa=0.730). This is because there are many narrow bands in the visible region and rich subtle spectral information available in the HYP hyperspectral sensor data. In spite of IKO's high spatial resolution, the mapping results with IKO data have the lowest accuracies due to high inner spectral variation in individual classes. For this issue, an object-based classification scheme may be hopeful to improve the mapping accuracy [8]. We will test this point later on. ALI outperformed TM for mapping seagrass in this study due to its additional blue band.

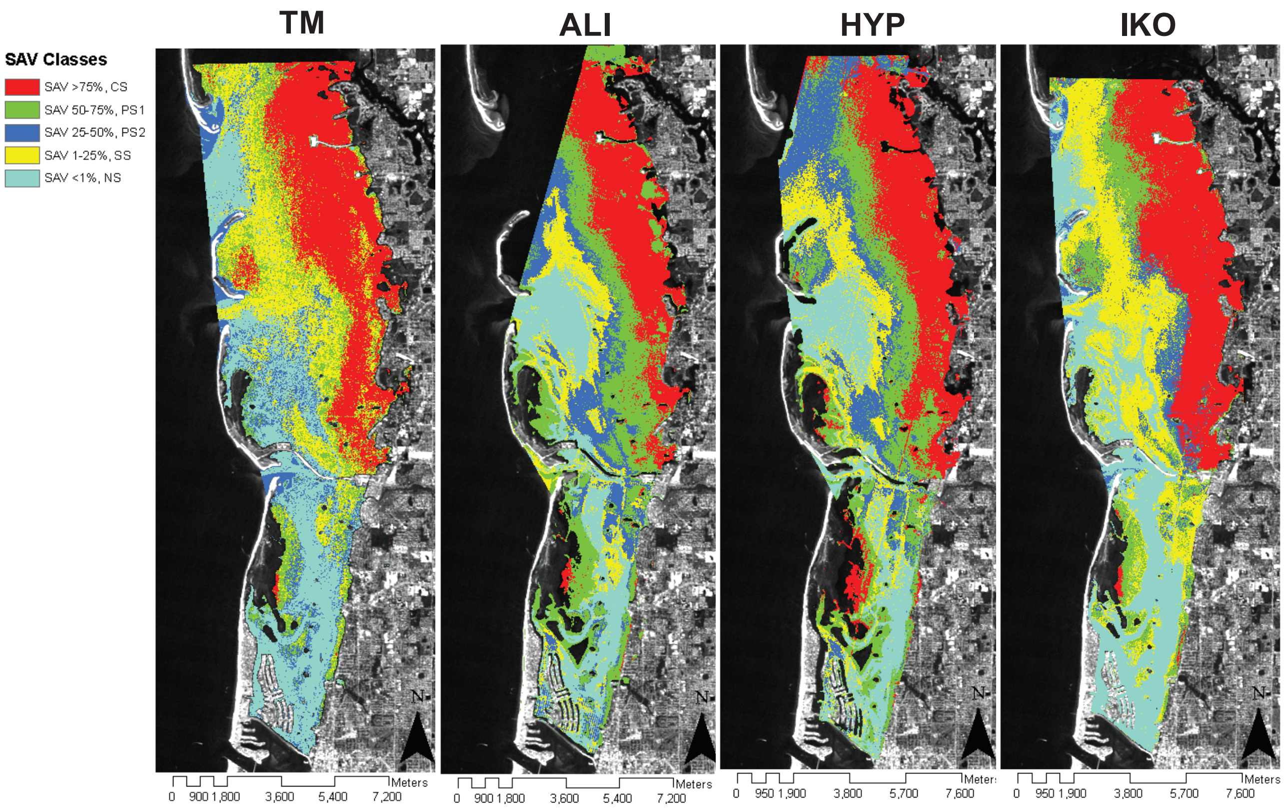

Figure 1. Classification results for the 5-class scheme with the four sensor image data: TM, ALI, HYP and IKO.

6. REFERENCES

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